Combined influence of forearm orientation and muscular contraction on EMG pattern recognition

Citation for published version:
Khushaba, RN, Al-Timemy, A, Kodagoda, S & Nazarpour, K 2016, 'Combined influence of forearm orientation and muscular contraction on EMG pattern recognition', *Expert Systems with Applications*, vol. 61, pp. 154-161. https://doi.org/10.1016/j.eswa.2016.05.031

Digital Object Identifier (DOI):
10.1016/j.eswa.2016.05.031

Published In:
Expert Systems with Applications

Expert Systems With Applications 61 (2016) 154–161

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Combined influence of forearm orientation and muscular contraction on EMG pattern recognition

Rami N. Khushaba[a,*], Ali Al-Timemy[b,c], Sarath Kodagoda[a], Kianoush Nazarpour[d,e]

[a] Faculty of Engineering and Information Technology, University of Technology, Sydney, Australia
[b] Department of Biomedical Engineering, Al-Khwarizmi College of Engineering, University of Baghdad, Iraq
[c] Center for Robotics and Neural Systems (CRNS), Plymouth University, UK
[d] School of Electrical and Electronic Engineering, Newcastle University, Newcastle-upon-Tyne NE1 7RU, UK
[e] Institute of Neuroscience, Newcastle University, Newcastle-upon-Tyne NE2 4HH, UK

ARTICLE INFO

Article history:
Received 26 January 2016
Revised 18 May 2016
Accepted 18 May 2016
Available online 20 May 2016

Keywords:
Accelerometer
EMG
Generalizability
Pattern recognition

ABSTRACT

The performance of intelligent electromyogram (EMG)-driven prostheses, functioning as artificial alternatives to missing limbs, is influenced by several dynamic factors including: electrode position shift, varying muscle contraction level, forearm orientation, and limb position. The impact of these factors on EMG pattern recognition has been previously studied in isolation, with the combined effect of these factors being understudied. However, it is likely that a combination of these factors influences the accuracy. We investigated the combined effect of two dynamic factors, namely, forearm orientation and muscle contraction levels, on the generalizability of the EMG pattern recognition. A number of recent time- and frequency-domain EMG features were utilized to study the EMG classification accuracy. Twelve intact-limbed and one bilateral transradial (below-elbow) amputee subject were recruited. They performed six classes of wrist and hand movements at three muscular contraction levels with three forearm orientations (nine conditions). Results indicate that a classifier trained by features that quantify the angle, rather than amplitude, of the muscle activation patterns perform better than other feature sets across different contraction levels and forearm orientations. In addition, a classifier trained with the EMG signals collected at multiple forearm orientations with medium muscular contractions can generalize well and achieve classification accuracies of up to 91%. Furthermore, inclusion of an accelerometer to monitor wrist movement further improved the EMG classification accuracy. The results indicate that the proposed methodology has the potential to improve robustness of myoelectric pattern recognition.

1. Introduction

An artificial hand is an example of a technology that can be used to help a person, with a congenital condition or after an injury that results in the loss of the limb, perform essential activities of daily living (Nazarpour, Cipriani, Farina, & Kuiken, 2014). Nowadays, commercial prosthetic hands are highly sophisticated, offering individual finger movement. These prosthetic hands are controlled with an intelligent interface that infers movement intentions by deciphering the electrical activity of muscles, known as the surface electromyogram (EMG) signal. The EMG signals are recorded non-invasively from the skin surface of the remaining arm to which the prosthesis is attached. Myoelectric interfaces based on EMG pattern recognition have gained considerable attention thanks to their naturalness enabling human intentions to be conveyed to control a machine.

EMG pattern recognition has been adopted in academic and commercial research, showing improvements in the control of hand prostheses (Al-Timemy, Bugmann, Escudero, & Outram, 2013a; Asghari Oskoei & Hu, 2007; Atzori et al., 2014; Kuiken, Turner, Soltys, & Dumanian, 2014; Nazarpour, Sharafat, & Firoozabadi, 2007; Zardoshti-Kermani, Wheeler, Badie, & Hashemi, 1995). In this framework, a natural map from users' limb motion to analogous, but discrete, prostheses function is formed by extracting the movement intent from multi-channel EMG signals. A significant amount of research has been devoted to various aspects of EMG pattern classification systems such as preprocessing and filtering, feature extraction and reduction and classification (Boostani & Moradi, 2003; Phinyomark et al., 2013). A number of studies have produced promising results in terms of classifica-

* Corresponding author. Tel: +44 (0) 191 208 6860; Fax: +44 (0) 191 208 8180.
E-mail addresses: rkhushab@gmail.com, Rami.Khushaba@uts.edu.au (R.N. Khushaba), Kianoush.Nazarpour@newcastle.ac.uk (K. Nazarpour).

http://dx.doi.org/10.1016/j.eswa.2016.05.031

tion accuracy (generally >90%) and real-time performance (Rasool, Iqbal, Bouaynaya, & White, 2016). However, despite encouraging demonstrations, translation of this research into the clinic has been limited (Jiang, Dosen, Müller, & Farina, 2012; Kuiken et al., 2014). This shortcoming may be because it is very difficult for the amputees to generate distinct activity patterns for different movement classes of hand or wrist movements. This will lead to overlap of the movement classes in the feature space which will in turn impair the classification. Advanced machine learning with induced artificial variability or, perhaps, with daily recalibration may improve the accuracy (Liu, Sheng, Zhang, He, & Zhu, 2016). However, because it is not clinically viable to emulate all possible variations, during prosthesis use, incorrect classifications will likely take place in response to EMG patterns that were not observed during training or recalibration.

Moreover, EMG pattern recognition performance is influenced by many factors including, but not limited to, change in limb position (with respect to the body) (Fougner, Scheme, Chan, Englehart, & Stavdahl, 2011; Park, Suk, & Lee, 2016), shift in EMG electrode location (Hargrove, Englehart, & Hudgins, 2008; Spanias, Perreault, & Hargrove, 2016), change of forearm orientation (Peng et al., 2013), varying the muscular contraction force level (Al-Timemy, Bugmann, Escudero, & Outram, 2013b; Al-Timemy, Khushaba, Bugmann, & Escudero, 2015; He, Zhang, Sheng, Li, Zhu, 2015), and the changing characteristics of the myoelectric signals itself over a long time (He et al., 2015; Liu, Zhang, Sheng, & Zhu, 2015), that in turn makes the long term myoelectric control an open challenge. MacIsaac et al. (MacIsaac, Parker, Scott, Englehart, & Duffley, 2001), tested the effect of joint angle and muscle contraction levels individually by estimating the EMG mean frequency and conduction velocity. They showed that both factors contribute to the variability observed in EMG parameter estimation, with the effect of joint angle variation being more dominant than that of the force level. Similarly, Tkach et al. (Tkach, Huang, & Kuiken, 2010) investigated the individual effects of electrode movement, variation in muscle contraction effort, and fatigue on the EMG pattern recognition accuracy. They showed that muscle fatigue has the smallest effect whereas electrode movement and force level variations can significantly affect the accuracy. In addition, several research groups have studied isolated effects of the forearm posture, position, and orientation (Fougner et al., 2011; Peng et al., 2013). They showed that with employing accelerometers and using training data from all positions that the user expects to encounter during real-time usage (Fougner et al., 2011; Peng et al., 2013) the isolated effect of forearm posture, position, and orientation can be reduced. Furthermore, Yang et al. (Yang, Yang, Huang, & Liu, 2015) reported that paradigms in which the EMG signals are collected during dynamic arm postures with varying muscular contractions can largely reduce the misclassification rate. However they only used the mean absolute value of the EMG signals as feature and hence the effectiveness of other feature extraction methods was not quantified.

Previous research quantified the effect of dynamic factors on EMG pattern recognition performance in isolation. In this paper, we investigate the *combined* effect of multiple dynamic factors. We consider varying the muscle contraction efforts, the first dynamic factor, across three levels along each of three different forearm orientations, the second dynamic factor. We further study the classification performance at each contraction level and forearm orientation with a number of time- and frequency-based EMG features. This is a novel analysis step; not previously utilized in this direction with multiple factors. Recently, we introduced power spectral descriptor features of the EMG signals to mitigate the impact of muscular contraction levels on EMG power spectrum characteristics (Al-Timemy et al., 2015). Here, we compare the classification performance of this and five other EMG and accelerometry features. In addition, we test generalizability of the classification across different forearm orientations and muscle contraction efforts. A preliminary version of this work was reported in (Khushaba, Al-Timemy, & Kodagoda, 2015).

In Section 2, we present the methods of recording and analysis of the EMG signals and the details of our generalization protocols. Results are reported in Section 3, before we discuss their significance and conclude in Section 4.

2. Methods

2.1. Subjects

Twelve intact-limbed and one bilateral amputee subjects (age range: 20–33 years, 1 female) with average forearm circumference of 26.59 ± 2.41 cm, participated in this study. At the time of the experiment, the amputee subject (30 years old male) had lived for six years with his condition.

Data for ten of the able-bodied subjects was collected at University of Technology, Sydney, Australia. Data from the three subjects (including one amputee subject) was collected in Babylon and Baghdad, Iraq. Participants had no previous experience with EMG-controlled interfaces. Subjects were introduced to the system in a 20-min briefing session before the main experiment.

All participants observed the corresponding university's research ethics committee approvals and gave informed consent to participate in the study.

2.2. Data acquisition

Data recorded in Australia: Data from six EMG electrodes was recorded with a Bagnoli desktop EMG system (Delsys Inc., USA), with a gain of 1000. Electrodes were equally spaced across the circumference of the forearm for the intact-limbed as shown in Fig. 1a. A 2-slot adhesive skin interface was applied on each of the sensors to firmly attach them to the skin. A conductive adhesive reference electrode (dermatrode reference electrode) was placed near the subjects' wrist. An additional 3-D accelerometer (MPU-6050 from InvenSense) was attached to the participants' wrist as shown in Fig. 1a to record wrist acceleration. A 12-bit analog-to-digital converter (National Instruments, BNC-2090) was used to sample the signal at 4000 Hz. The accelerometer data was resampled to match the sampling rate of the EMG signals, with an original sampling rate of 26.6 ± 0.3Hz.

Data recorded in Iraq: Data was recorded from three subjects in Iraq, one bilateral amputee and two intact-limbed subjects. Skin was first prepared with an abrasive gel (NuPrep, USA). For the amputee subject, eight pairs of Ag/AgCl electrodes (Tyco Healthcare GmbH, Germany) were placed around the amputee's right stump (Fig. 1b) and connected to an EMG amplifier (built in-house). As for the other two intact-limbed subjects, the EMG sensors were placed on the forearm. The EMG signals were then amplified with a custom built amplifier (gain: 1000), bandpass filtered between 20–450 Hz with a 50Hz notch filter, and sampled at a rate of 2,000 Hz with a 16-bit ADC (National Instruments NI USB-6210). A Labview-based software was developed to acquire and display the EMG signals. All recorded signals were analyzed using MATLAB®(Mathworks, USA).

2.3. Experimental protocol

Subjects sat in front of a standard computer screen. They performed six classes (C1-C6) of movements, namely, hand close (C1), hand open (C2), wrist extension (C3), wrist flexion (C4), wrist ulnar deviation (C5), and wrist radial deviation (C6).

We considered three forearm orientations: wrist fully supinated, at rest, and fully pronated, denoted by Orienta-

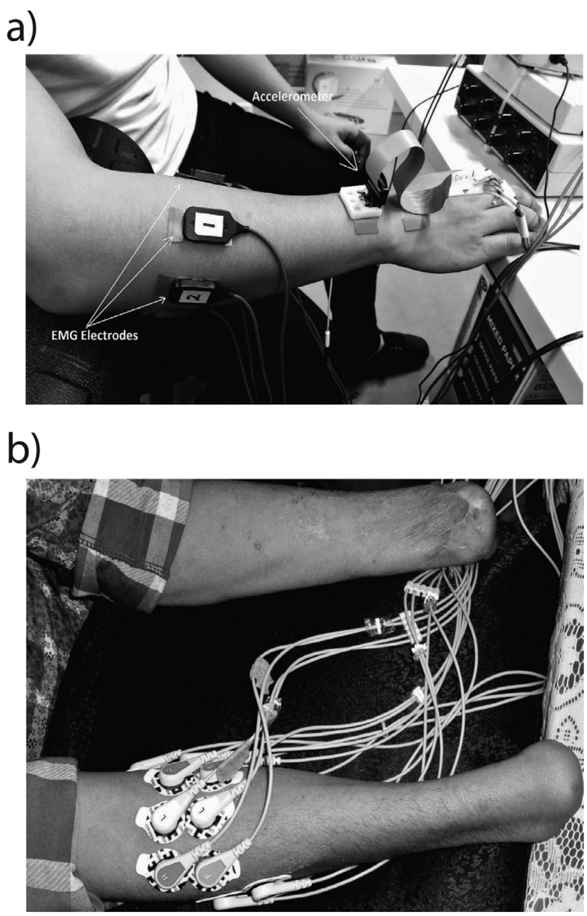

Fig. 1. (a) Configuration of the EMG electrodes and the wrist accelerometry sensor on the forearm of an intact-limbed subject; (b) the placement of the EMG electrodes on the amputee's stump .

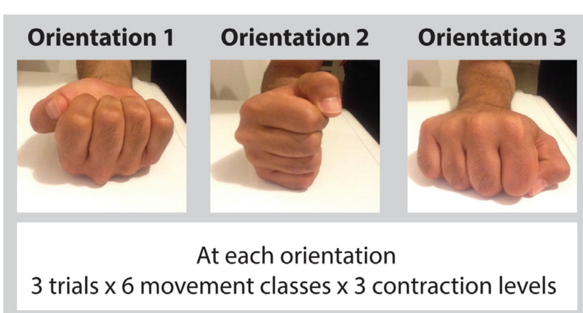

Fig. 2. The three forearm orientations at which subjects performed the six classes of movements, each at three muscular contraction levels.

tions 1 to 3 in Fig. 2. At each orientation, subjects repeated all six movements at three different muscular contraction levels: low, medium, and high. Three trials for each movement were recorded, with each beginning with the low contraction level and gradually increasing the intensity of contraction. Instructions appeared clearly on the computer screen using an image of the desired movement along with a text caption.

In total, 162 trials per subject were collected: 6 movement classes × 3 forearm orientations × 3 contraction levels × 3 trials per movement. The number of conditions was selected such that experiment remains short, and yet, it would be possible to conduct statistical analysis. To avoid fatigue, each trial lasted 5 s and subjects had up to 10 s of rest between trials.

The loss of proprioceptive feedback from the hand after amputation can make the task very challenging for the amputee subjects (Pistohl, Joshi, Ganesh, Jackson, & Nazarpour, 2015). We therefore showed the raw EMG signals on the screen to help the amputee to generate the movement with the required muscular contraction level.

2.4. Data analysis

We investigated the combined effect of forearm orientation and muscle contraction level on the generalizability of the EMG pattern recognition. We therefore defined two schemes:

1. *Within-orientation generalizability*, in which we evaluated the classification performance when the training and testing data were selected from the *same* forearm orientation condition; and
2. *Between-orientation generalizability*, in which the classifier was trained and tested with data recorded in *different* orientation conditions.

2.5. Feature extraction

We investigated the effect of the extracted features on the generalizability of the EMG pattern recognition. Using an overlapping window size of 150 ms with 75 ms increments (50% overlap), we extracted the following features:

1. Wavelet transform-based features: The Symmlet family with five decomposition levels =was used. Features were the logarithm of the mean of the squared wavelet coefficients at each level (Asghari Oskoei & Hu, 2007; Phinyomark, Limsakul, & Phukpattaranont, 2011);
2. Time-domain (TD) features: comprising root mean square (RMS), waveform length (WL), number of zero-crossings (ZC), slope sign change (SSC) and mean absolute value (MAV) (Hakonena, Piitulainenb, & Visala, 2015; Tenore et al., 2009);
3. TDAR1: a combination of the RMS feature and $5th-$order autoregressive (AR) coefficients (Chan & Green, 2007).
4. TDAR2: a combination of sample entropy (SE), WL, fourth order cepstrum coefficients and the $5th-$order AR coefficients.
5. Discrete Fourier transform based features (DFT) (He et al., 2015);
6. Time-domain power spectral descriptors (TD-PSD) (Al-Timemy et al., 2015; Khushaba, Takruri, Miro, & Kodagoda, 2014);

Feature sets 1 to 4 have been used in myoelectric control widely (Boostani & Moradi, 2003; Hakonena et al., 2015). The DFT (5) and TD-PSD (6) features were recently proposed in (Al-Timemy et al., 2015; He et al., 2015; Khushaba et al., 2014). In the interest of completeness we briefly review the underlying concepts of the DFT and TD-PSD features. The interested reader is referred to (Al-Timemy et al., 2015; He et al., 2015; Khushaba et al., 2014) for further information.

The DFT and TD-PSD features form a set of invariants to force level variations in two steps: (1) a set of features describing the EMG power spectrum are extracted either from the EMG power spectrum, for DFT features, or directly from the time-domain signal, for TD-PSD; (2) a cosine similarity function is employed to estimate the angle between the extracted power spectrum characteristics from the original EMG signals and their non-linear version in TD-PSD, while the DFT method considers the angle between force levels within each of predefined frequency bands. The resulting vector is then used as the final feature set. This mechanism has proven robust to the variability caused by force level variations on the intact-limbed (He et al., 2015) and amputees (Al-Timemy et al., 2015), with TD-PSD offering more powerful solutions for amputees, while performing equivalently to DFT on intact-limbed subjects.

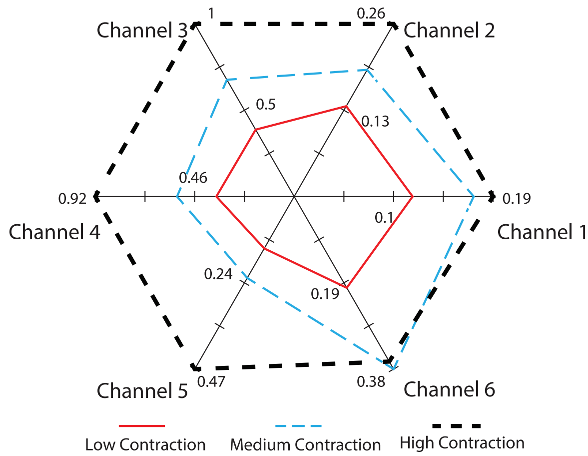

Fig. 3. An example of the RMS of the EMG signals from six channels during a wrist flexion movement at three different levels.

Furthermore, we investigated the potential enhancement of the classification accuracy when the RMS of the accelerometry sensor signal was included as an additional element in the above feature vectors.

2.6. Classification

We used a support vector machine (SVM) classifier with a radial basis kernel. Parameters were optimized based on training accuracy: $C = 32$ and $\gamma = 0.0625$. The utilized SVM classifier performed comparably to linear discriminant analysis (LDA) classifier.

2.7. Statistical analysis

To test the statistical significance of our results, we carried out repeated measures ANOVA, unless stated otherwise. Where required, post-hoc analysis with a Bonferroni correction was performed. Significance level was set to 0.05. All statistical analysis were performed in IBM®SPSS Statistics (ver. 21).

3. Experimental results

In reporting the results, we first combine all results from all subjects ($n = 13$). Following that we report the classification results for the amputee subject. Finally, we investigate the relative information in the EMG and accelerometer features in Section 3.5.

3.1. Generation of graded muscular contraction levels

We first verified whether the subjects could produce EMG activity in all different classes of movement at three muscular contraction levels (low, medium, and high). This was carried out by analyzing the RMS of EMG activity across all channels, orientations and movements. Fig. 3 depicts a representative radar plot of the EMG signals RMS values collected from one subject performing wrist flexion (C4) when the wrist was fully pronated (Orientation 3). The RMS values from the different channels were then grouped in separate columns for each force level, thereby constructing an RMS matrix. A one-way ANOVA was utilized to validate statistical significance, treating each column of the RMS matrix as a separate group. We determined whether the population means of the columns are equal. A significant difference between the means of the different force levels was observed ($p = 0.003$).

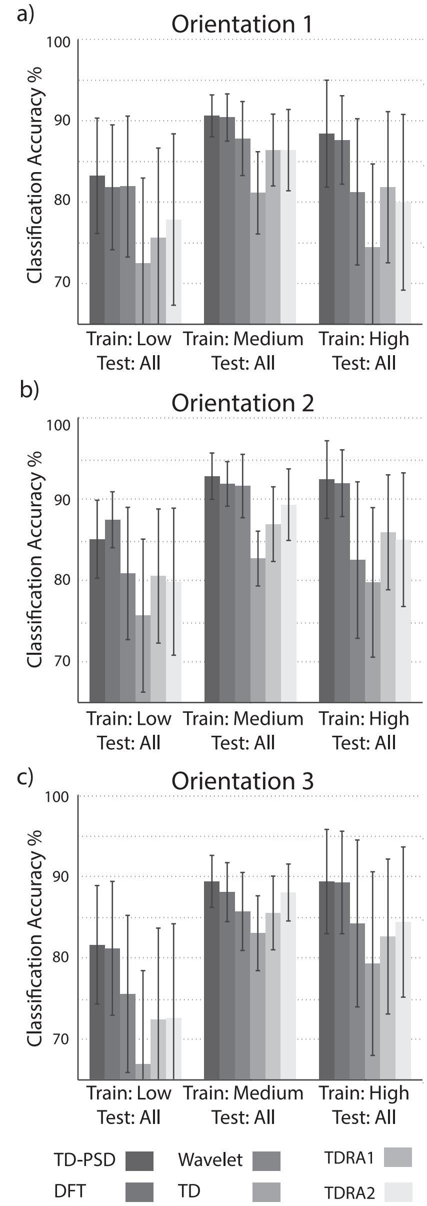

Fig. 4. Within-orientations generalization results averaged across all subjects; with training data from a specific contraction level and testing data from all possible contraction levels in each of orientations 1 (a), 2 (b) and 3 (c) as introduced in Fig. 2. Error bars represent the standard error.

3.2. Within-orientation generalization

At each orientation condition, we compared the performance of different feature sets when the classifier was trained with data recorded on a certain contraction level and was tested with data from all possible force levels. We selected the first two trials for training and the third was used for testing. The results of this experiment are shown in Fig. 4. An 3-by-6 (orientations-by-features) ANOVA with repeated measures showed that there is no significant difference between the classification scores achieved in different forearm orientations ($n = 13, F_{2,24} = 3.08, p = 0.06$).

We however observed a significant effect of the extracted features ($n = 13, F_{1.78,21.39} = 10.03, p < 10^{-3}$, Greenhouse-Geisser-corrected). Bonferroni corrected post-hoc pairwise comparisons showed that the TD-PSD features result in significantly higher classification scores when compared to the TD (difference: 10.82%, $p = 0.01$), TDAR (difference: 5.9%, $p = 0.01$) and TDAR2 (difference:

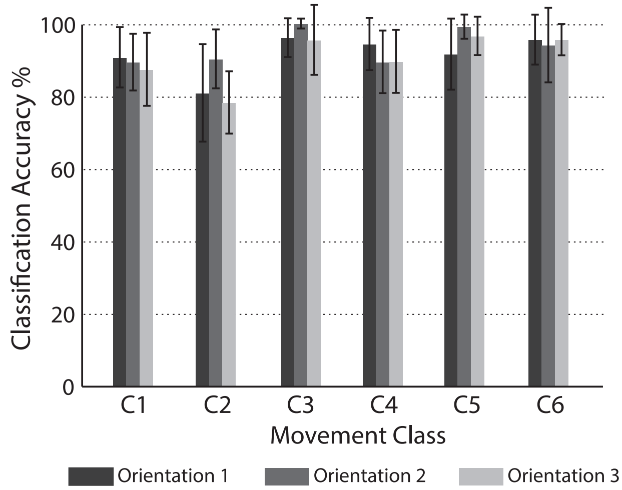

Fig. 5. Class-wise classification accuracy results, averaged across all subjects, using the TD-PSD features when training and testing data was acquired from the same forearm orientation. Error bars represent the standard errors.

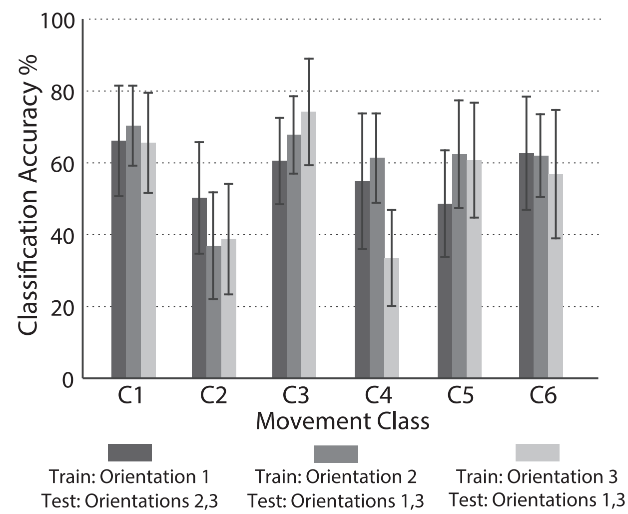

Fig. 6. Class-wise classification accuracy, averaged across all subjects, using the TD-PSD features when the training and testing data was acquired from different forearm orientations. Error bars represent the standard errors.

5.7%, $p = 0.02$) features. However, the difference between the results achieved by the TD-PSD, the DFT and the wavelet transform were statistically insignificant ($p > 0.05$). Interestingly, DFT features outperformed the classic TD features by 10.46% ($p = 0.04$). As the TD-PSD feature set has previously shown to outperform DFT and other feature sets when tested on a group of amputees, we applied only TD-PSD for the remaining of the within-orientation analysis. Classification resulted in higher accuracies when the training data was collected at medium contraction efforts (Fig. 4).

We investigated the classification accuracy of individual movement classes with the TD-PSD features (Fig. 5). A 3-by-6 (orientations-by-class), ANOVA with repeated measures showed no differences across the three forearm orientations ($n = 13, F_{2,17} = 0.47, p = 0.63$), despite the observed differences in the class-wise recognition results.

3.3. Between-orientation generalization

We considered training the classifier with the TD-PSD features extracted from data collected in all contraction levels within a specific forearm orientation. We then tested the classifier with data from all contraction levels within the remaining orientations, that is, the training and testing samples were from different orientations.

The performance of the classifier in this case dropped significantly when compared to the case when the training and testing data was collected at the same forearm orientation ($n = 13, F_{1,35} = 96.37, p < 10^{-3}$). Results are shown in Fig. 6. This finding is in line with the earlier work of Fougner et al. (2011).

We further investigated the between-orientation generalization by repeating the classification for all feature sets according to the muscular contraction levels. To that end, the classifier was trained with data recorded at a certain contraction level from all orientations. Then it was tested with data from all muscular contraction levels from all orientations. In other words, both the training and testing data were from all orientations.

Classification scored are shown in Fig. 7. Statistical tests revealed the main effects of training data (ANOVA, repeated measures, $n = 13$, $F_{2,24} = 20.3$, $p < 10^{-3}$) and the extracted features (ANOVA, repeated measures, corrected with Greenhouse-Geisser, $n = 13$, $F_{2.12,25.48} = 10.41$, $p < 10^{-3}$). A pair-wise post-hoc analysis of the main effect of the training data showed that the classifier achieved the highest classification results when trained with data

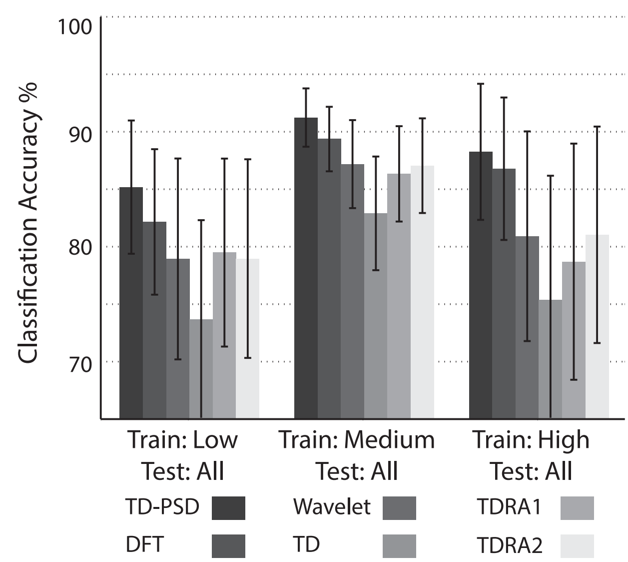

Fig. 7. Between-orientations generalization averaged across all subjects; with training data from one contraction level from all orientations, and testing data from all contraction levels in all orientations. Error bars represent the standard error.

recorded at medium contraction level (medium-low difference: 7.6%, $p < 10^{-3}$) and (medium-high difference: 5.6%, $p = 0.002$).

A pair-wise post-hoc analysis of the main effect of the extracted features revealed that the scores achieved with the TD-PSD feature were significantly higher than that of all other features $p < 10^{-3}$, but the DFT feature (difference: 2.21%, $p = 0.34$). In addition, the performance achieved with the DFT feature was significantly better than that achieved with the TD features only (difference: 8.79%, $p = 0.03$). All other differences were statistically insignificant ($p > 0.05$).

Fig. 8 illustrates the average confusion matrix of the classification results across all subjects with the TD-PSD features achieved at medium contraction levels. Between all classes, C2 (Hand Open) showed the largest error. The misclassification of C2 in this case might be because of the variability of opening with different contraction level. It may be that with further training, and with visual feedback, these results can be further enhanced across all forearm orientations and muscular contraction levels.

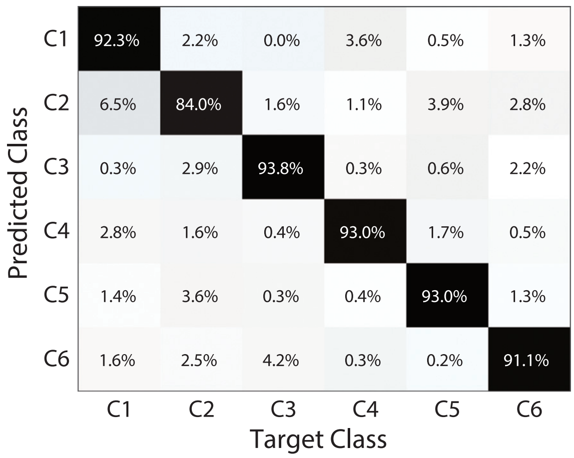

Fig. 8. A representative classification confusion matrix when training with the medium contraction level data and testing with all contraction levels and all orientations.

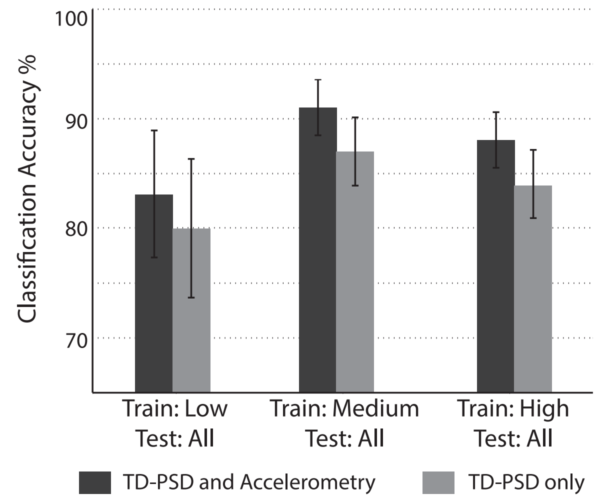

Fig. 9. Relative information in the EMG and accelerometer features. Inclusion of the accelerometer data improves the classification accuracy.

Table 1
Classification accuracy of the amputee subject's data only with TD-PSD and DFT features, with training and testing data from all contraction levels within each forearm orientation.

	Test orientation1	Test orientation2	Test orientation3
Train Orientation1	**TD-PSD 90.2%** DFT 84.9%	**TD-PSD 72.6%** DFT 62.6%	**TD-PSD 48.6%** DFT 43.9%
Train Orientation2	**TD-PSD 79.4%** DFT 55.3%	**TD-PSD 95.8%** DFT 95.7%	TD-PSD 55.1% **DFT 58.2%**
Train Orientation3	**TD-PSD 66.6%** DFT 54.2%	**TD-PSD 68.5%** DFT 68.1%	**TD-PSD 96.6%** DFT 96.5%

Table 2
Classification accuracy of the amputee subject's data only with TD-PSD and DFT features, with training and testing data from all forearm orientations within each specific contraction level.

	Test Low	Test Med	Test High
Train Low	**TD-PSD 93.2%** DFT 88.4%	**TD-PSD 85.4%** DFT 77.3%	**TD-PSD 83.0%** DFT 75.3%
Train Med	**TD-PSD 91.7%** DFT 86.0%	**TD-PSD 90.5%** DFT 81.9%	**TD-PSD 73.1%** DFT 71.3%
Train High	**TD-PSD 81.1%** DFT 68.7%	**TD-PSD 93.4%** DFT 78.0%	**TD-PSD 93.1%** DFT 87.5%

3.4. Classification results for the amputee subject

Finally, we report the classification scores for the amputee subject in the following two scenarios:

1. With the classifiers trained based on data of all contraction levels within each orientation and tested based on data of all muscular contraction levels from other orientations. The overall accuracy results for this scenario are shown in Table 1;
2. With training and testing data that belong to all orientations for each contraction level. The overall accuracy results for this scenario are shown in Table 2.

The results in both tables are given for the TD-PSD and the DFT features only, as these were the most promising features in terms of generalization capability as demonstrated in Fig. 7.

3.5. Relative information in the EMG and accelerometer data

We quantified the benefit of including the accelerometry information in the classification. We used data from subjects for whom the accelerometry data was recorded. The mean classification performance averaged across ten subjects and orientations for the three contraction level train-testing conditions are shown in Fig. 9. The classification accuracy when using the combined TD-PSD and accelerometer features was significantly higher than that with the TD-PSD features only condition (ANOVA, repeated measures, $n = 10,\ F_{1,9} = 31.37,\ p < 10^{-4}$).

4. Concluding remarks

With using a subset of well-known EMG feature extraction, we studeid the effects of combined effect of forearm orientation and muscular contraction level on the performance of EMG pattern recognition. Both of the TD-PSD and DFT features were previously used in (Al-Timemy et al., 2015; He et al., 2015) to reduce the effect of varying the contraction level on the classification accuracy of the EMG signals. However, neither of these feature sets were tested previously in experiments with more than one dynamic factor affecting the EMG signals. Our results show that the recently proposed TD-PSD and DFT features are superior, in terms of classification accuracy, to other features; with a tendency for the TD-PSD feature to produce higher results. Training the classifier with data from different forearm orientations and using the TD-PSD and DFT features offered promising solutions to the problem of identifying the hand and wrist movements when performed at different orientations and muscular contraction levels.

Analysis of the amputee data suggested, predictably, that training and testing a classifier with the data collected at the same forearm orientation provides the highest scores. In addition, our results showed that there is a considerable advantage in including data from all orientations in the training set to support the classifier with generalizability to novel data.

These results indicate that when training a classifier with data with low or high contraction levels, the classifier can generalize reasonably to other conditions. In addition, we showed that training the classifier with data recorded at medium contraction levels can significantly enhance generalization on novel data with medium and low contraction conditions, but not at the high contraction level. For amputees, generating large-amplitude EMGs for a long time may become very tiring, as they may have not used their muscles for a long time. Therefore, it is more practical to train the amputees on gestures at low or medium contraction levels to avoid fatigue and indeed misclassification. Moreover, our results suggest that changing the forearm orientation has a more profound impact on the classification results than changing the muscular contraction levels (Figs. 5 and 6). Specifically, Fig. 5 showed no differences between the classification accuracy results when the training and testing data were acquired from the same orientation. However, training and testing on data from different orientations affected the classification results significantly (Fig. 6). Thus, the collection of training data from multiple orientations was necessary to enhance generalization (Fig. 7).

The presented results suggest several future research directions to further improve the performance of myoelectric-driven intelligent systems:

- More efforts should be directed towards advancing the methods of feature extraction to overcome the influence of dynamic factors that limit the performance. The use of advanced machine learning methods such as deep neural networks and muscles synergies extraction should also be investigated on problems under the influence of multiple dynamic factors as such methods may provide substantial improvements upon the utilized time-and-frequency EMG feature extraction methods (Diener, Janke, & Schultz, 2015; Ison, Vujaklija, Whitsell, Farina, & Artemiadis, 2016; Park & Lee, 2016). Meanwhile, we showed that the performance of the learning algorithms can be improved by using feature extraction methods that rely on the angular information of muscle activation patterns. Features such as the TD-PSD and the DFT proved more successful than others in reducing the impact of the two dynamic factors that we considered in this paper. Such features can be readily implemented into a prosthesis controller for real-time control, especially that the EMG pattern recognition systems are nowadays becoming available for clinical testing, e.g. the COAPT complete control system (Kuiken et al., 2014)[1].
- More research efforts should be directed to investigate whether accelerometry could provide a reliable alternative or complementary medium for motor intention detection when the quality of the EMG signal deteriorates under many circumstances such as altered skin conditions, temperature change and sweat (Asghari Oskoei & Hu, 2007; Farina et al., 2014; Jiang et al., 2012). We provided evidence that the inclusion of accelerometry information can significantly improve the classification scores in our experiments. The use of accelerometry in EMG decoding was first proposed by (Fougner et al., 2011; Scheme, Fougner, Stavdahl, Chan, & Englehart, 2010). They demonstrated that when data was collected under multiple limb positions, the use of accelerometry information yielded a significant improvement in motion classification accuracy. Our results are in line with the work of Atzori et al. (2014); Krasoulis, Vijayakumar, and Nazarpour (2015); Kyranou, Krasoulis, Erden, Nazarpour, and Vijayakumar (2016) who showed that inertial measurements, e.g. accelerometry, information can yield higher classification and finger movement reconstruction performance when compared to decoding with EMG-features only. This finding could have a remarkable impact in clinical applications, where the use of multi-modal information improves robustness by inducing redundancy.
- Moreover, we previously showed that it may be possible to control a prosthesis hand with arbitrary and abstract maps between upper-limb muscles and active joints of prosthetic hands, for example, grasping an object by contacting the index finger muscle only or by contracting a small group of muscles that do not control the grasp naturally (Pistohl, Cipraini, Jackson, & Nazarpour, 2013). Future research may include fusion of the EMG and accelerometry in abstract control interfaces to test whether subjects can learn to control the prosthesis with accelerometry data as well as they can with EMG.

Finally, the main strength of this paper was that it provided a pioneering evaluation into the combined effect of multiple dynamic factors on the EMG classification accuracy using different features. To the authors' knowledge this has not been previously investigated. On the other hand, it is also important to discuss a few points that may be considered as limitations of the proposed research method, including: Firstly, a small number of hand movements were considered in this work. It should be noted here that three trials for each of these movements were performed at each of the muscular contraction levels within each specific forearm orientation. Following that, the whole set was repeated for the remaining two forearm orientations. Despite the resting periods included between the trials, some of the recruited 13 subjects reported that the inclusion of any further hand movements could be fatiguing. Hence, we limited the experiment to six classes of movements only. Secondly, we recruited only one amputee subject in this study because the length of residual forearm of our other amputee volunteers was not adequate to study the effect of forearm orientation. We continue to recruit more amputees to study the influence of forearm orientation and muscular contraction levels on EMG pattern recognition.

Acknowledgment

The authors would like to thank Leo Shire and Adrian Abdipranoto for their help with the intact-limbed data collection process; Hai Li and Nicholas Outram for building the EMG amplifier used to collect the amputee EMG data. The work of K. Nazarpour is supported by the EPSRC, UK (grants: EP/M025977/1 and EP/M025594/1).

Data supporting this publication is not openly available due to ethical consideration(s). Access may be possible under appropriate agreement. Additional metadata record at http://dx.doi.org/10.17634/137930-2. Please contact Newcastle Research Data Service at rdm@ncl.ac.uk for further information or access requests.

References

Al-Timemy, A. H., Bugmann, G., Escudero, J., & Outram, N. (2013a). Classification of finger movements for the dexterous hand prosthesis control with surface electromyography. *IEEE Journal of Biomedical and Health Informatics, 17*(3), 608–618. doi:10.1109/JBHI.2013.2249590.

Al-Timemy, A. H., Bugmann, G., Escudero, J., & Outram, N. (2013b). A preliminary investigation of the effect of force variation for the control of hand prosthesis. In *Proceedings of the 35th Annual International Conference of the IEEE EMBS (EMBC'13), Osaka, Japan* (pp. 5758–5761). doi:10.1109/EMBC.2013.6610859.

Al-Timemy, A. H., Khushaba, R. N., Bugmann, G., & Escudero, J. (2015). Improving the performance against force variation of EMG controlled multifunctional upper-limb prostheses for transradial amputees. *IEEE Transactons on Neural Systems and Rehabilitation Enginerring*. doi:10.1109/TNSRE.2015.2445634. Epub ahead of print.

Asghari Oskoei, M., & Hu, H. (2007). Myoelectric control systems – A survey. *Biomedical Signal Processing and Control, 2*(4), 275–294. doi:10.1016/j.bspc.2007.07.009.

Atzori, M., Gijsberts, A., Castellini, C., Caputo, B., Hager, A.-G. M., Elsig, S., … Müller, H. (2014). Electromyography data for non-invasive naturally-controlled robotic hand prostheses. *Scientific Data, 1*, 140053. doi:10.1038/sdata.2014.53.

Boostani, R., & Moradi, M. H. (2003). Evaluation of the forearm EMG signal features for the control of a prosthetic hand. *Physiological Measurement, 24*(22), 309–319. doi:10.1088/0967-3334/24/2/307.

Chan, A. D. C., & Green, G. C. (2007). Myoelectric control development toolbox. In *Proceedings of 30th conference of the canadian medical and biological engineering society, toronto, canada*. M0100–1 – M0100–4

Diener, L., Janke, M., & Schultz, T. (2015). Direct conversion from facial myoelectric signals to speech using deep neural networks. In *Proceedings of the international joint conference on neural networks (IJCNN), Killarney, Ireland* (pp. 1–7).

[1] https://www.coaptengineering.com/

Farina, D., Jiang, N., Rehbaum, H., Holobar, A., Graimann, B., Dietl, H., & Aszmann, O. C. (2014). The extraction of neural information from the surface EMG for the control of upper-limb prostheses: emerging avenues and challenges. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 22*(4), 797–809. doi:10.1109/TNSRE.2014.2305111.

Fougner, A., Scheme, E., Chan, A. D. C., Englehart, K., & Stavdahl, Ø. (2011). Resolving the limb position effect in myoelectric pattern recognition. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 19*(6), 644–651. doi:10.1109/TNSRE.2011.2163529.

Hakonena, M., Piitulainenb, H., & Visala, A. (2015). Current state of digital signal processing in myoelectric interfaces and related applications. *Biomedical Signal Processesing and Control, 18*(2), 334–359. doi:10.1016/j.bspc.2015.02.009.

Hargrove, L., Englehart, K., & Hudgins, B. (2008). A training strategy to reduce classification degradation due to electrode displacements in pattern recognition based myoelectric control. *Biomedical Signal Processesing and Control, 3*(2), 175–180. doi:10.1016/j.bspc.2007.11.005.

He, J., Zhang, D., Jiang, N., Sheng, X., Farina, D., & Zhu, X. (2015). User adaptation in long-term, open-loop myoelectric training: implications for EMG pattern recognition in prosthesis control. *Journal of Neural Engineering, 12*(4), 046005. doi:10.1088/1741-2560/12/4/046005.

He, J., Zhang, D., Sheng, X., Li, S., & Zhu, X. (2015). Invariant surface EMG feature against varying contraction level for myoelectric control-based on muscle coordination. *IEEE Journal of Biomedical and Health Informatics, 19*(3), 874–882. doi:10.1109/JBHI.2014.2330356.

Ison, M., Vujaklija, I., Whitsell, B., Farina, D., & Artemiadis, P. (2016). High-density electromyography and motor skill learning for robust long-term control of a 7-DoF robot arm. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 4*(24), 424–433. doi:10.1109/TNSRE.2015.2417775.

Jiang, N., Dosen, S., Müller, K. R., & Farina, D. (2012). Myoelectric control of artificial limbs- is there a need to change focus? *IEEE Signal Processing Magazine, 29*(5), 148–152. doi:10.1109/MSP.2012.2203480.

Khushaba, R. N., Al-Timemy, A., & Kodagoda, S. (2015). Influence of multiple dynamic factors on the performance of myoelectric pattern recognition. In *Proceedings of the 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC'15), Milano, Italy* (pp. 1679–1682).

Khushaba, R. N., Takruri, M., Miro, J. V., & Kodagoda, S. (2014). Toward limb position invariant myoelectric pattern recognition using time-dependent spectral features. *Neural Networks, 55*(4), 42–58. doi:10.1016/j.neunet.2014.03.010.

Krasoulis, A., Vijayakumar, S., & Nazarpour, K. (2015). Evaluation of regression methods for the continuous decoding of finger movement from surface EMG and accelerometry. In *Proceedings of IEEE Neural Engineering (NER'15), Montpellier, France* (pp. 631–634). doi:10.1109/NER.2015.7146702.

Kuiken, T. A., Turner, K., Soltys, N., & Dumanian, G. A. (2014). First clinical fitting of an individual after bilateral TMR with intuitive pattern recognition control. In *Proceedings of MyoElectric Controls symposium, Fredericton, New Brunswick, Canada* (pp. 121–124).

Kyranou, I., Krasoulis, A., Erden, M. S., Nazarpour, K., & Vijayakumar, S. (2016). Real–time classification of multi-modal sensory data for prosthetic hand control. In *Proceedings of IEEE International Conference on Biomedical Robotics and Biomechatronics (Biorob'16).*

Liu, J., Sheng, X., Zhang, D., He, J., & Zhu, X. (2016). Reduced daily recalibration of myoelectric prosthesis classifiers based on domain adaptation. *IEEE Journal of Biomedical and Health Informatics, 20*(1), 166–176. doi:10.1109/JBHI.2014.2380454.

Liu, J., Zhang, D., Sheng, X., & Zhu, X. (2015). Enhanced robustness of myoelectric pattern recognition to across-day variation through invariant feature extraction. In *37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC'15), Milano, Italy* (pp. 7262–7265).

MacIsaac, D. T., Parker, P. A., Scott, R. N., Englehart, K. B., & Duffley, C. (2001). Influences of dynamic factors on myoelectric parameters. *IEEE Engineering in Medicine and Biology Magazine, 20*(6), 82–89. doi:10.1109/51.982279.

Nazarpour, K., Cipriani, C., Farina, D., & Kuiken, T. (2014). Guest Editorial: Advances in control of multi-functional powered upper-limb prostheses. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 22*(4), 711–715. doi:10.1109/TNSRE.2014.2330451.

Nazarpour, K., Sharafat, A.-R., & Firoozabadi, S. M. P. (2007). Application of higher order statistics to surface electromyogram signal classification. *IEEE Transactions on Biomedical Engineering, 54*(10), 1762–1769. doi:10.1109/TBME.2007.894829.

Park, K. H., & Lee, S. W. (2016). Movement intention decoding based on deep learning for multiuser myoelectric interfaces. In *Proceedings of the 4th International Winter Conference on Brain-Computer Interface, Gangwon province, South Korea* (pp. 1–2). doi:10.1109/IWW-BCI.2016.7457459.

Park, K. H., Suk, H. I., & Lee, S. W. (2016). Position-independent decoding of movement intention for proportional myoelectric interfaces. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*. doi:10.1109/TNSRE.2015.2481461.

Peng, L., Hou, Z., Chen, Y., Wang, W., Tong, L., & Li, P. (2013). Combined use of semg and accelerometer in hand motion classification considering forearm rotation. In *Proceedings of the 35th Annual International Conference of the IEEE EMBS (EMBC'13), Osaka, Japan* (pp. 4227–4230). doi:10.1109/EMBC.2013.6610478.

Phinyomark, A., Limsakul, C., & Phukpattaranont, P. (2011). Application of wavelet analysis in EMG feature extraction for pattern classification. *Measurement Science Review, 11*(2), 45–52. doi:10.2478/v10048-011-0009.

Phinyomark, A., Quaine, F., Charbonnier, S., Serviere, C., Tarpin-Bernard, F., & Laurillau, Y. (2013). EMG feature evaluation for improving myoelectric pattern recognition robustness. *Expert Systems with Applications, 40*(12), 4832–4840. doi:10.1016/j.eswa.2013.02.023.

Pistohl, T., Cipraini, C., Jackson, A., & Nazarpour, K. (2013). Abstract and proportional myoelectric control for cursor and prosthetic hand. *Annals of Biomedical Engineering, 41*(12), 2687–2698. doi:10.1007/s10439-013-0876-5.

Pistohl, T., Joshi, D., Ganesh, G., Jackson, A., & Nazarpour, K. (2015). Artificial proprioceptive feedback for myoelectric control. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 23*(3), 498–507. doi:10.1109/TNSRE.2014.23558562.

Rasool, G., Iqbal, K., Bouaynaya, N., & White, G. (2016). Real-time task discrimination for myoelectric control employing task-specific muscle synergies. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 24*(1), 98–108. doi:10.1109/TNSRE.2015.2410176.

Scheme, E., Fougner, A., Stavdahl, Ø., Chan, A., & Englehart, K. (2010). Examining the adverse effects of limb position on pattern recognition based myoelectric control. In *Proceedings of the 32nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC'10)* (pp. 6337–6340).

Spanias, J. A., Perreault, E. J., & Hargrove, L. J. (2016). Detection of and compensation for EMG disturbances for powered lower limb prosthesis control. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 2*(24), 226–234. doi:10.1109/TNSRE.2015.2413393.

Tenore, F. V. G., Ramos, A., Fahmy, A., Acharya, S., Etienne-Cummings, R., & Thakor, N. V. (2009). Decoding of individuated finger movements using surface electromyography. *IEEE Transactions on Biomedical Engineering, 56*(5), 1427–1434. doi:10.1109/TBME.2008.2005485.

Tkach, D., Huang, H., & Kuiken, T. A. (2010). Study of stability of time-domain features for electromyographic pattern recognition. *Journal of NeuroEngineering Rehabilitation, 7*(21). doi:10.1186/1743-0003-7-21.

Yang, D., Yang, W., Huang, Q., & Liu, H. (2015). Classification of multiple finger motions during dynamic upper limb movements. *IEEE Journal of Biomedical Health Informatics*. doi:10.1109/JBHI.2015.2490718. Epub ahead of print.

Zardoshti-Kermani, M., Wheeler, B. C., Badie, K., & Hashemi, M.-R. (1995). EMG feature evaluation for movement control of upper extremity prostheses. *IEEE Transactions on Biomedical Engineering, 3*(4), 324–333. doi:10.1109/86.481972.